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Quantifying landscape externalities of renewable energy development: Implications of attribute cut-offs in choice experiments

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A B S T R A C T

Renewable energy is worldwide seen as a key element necessary to address climate change. However, finding socially acceptable locations for renewable energy facilities and the accompanying infrastructure increasingly often faces fierce opposition. This paper quantifies the landscape externalities of renewable energies employing a choice experiment. In addition, it is investigated how accounting for non-compensatory choice behavior, *i.e.* attribute cut-offs, affects welfare measures and subsequently policy recommendations. The empirical application is Germany where we conducted a nationwide survey on the development of renewable energies. We first show that cut-off elicitation questions prior to the choice experiment at least partially influence preferences. We further find that most participants state cut-off levels for attributes. Many are, however, at the same time willing to violate the self-imposed thresholds when choosing among the alternatives. To account for this effect, stated cut-offs are incorporated into a mixed logit model following the soft cut-off approach. Model results indicate substantial taste heterogeneity in preferences and in the use of cutoffs. Also, welfare estimates are substantially affected. We conclude that welfare changes from renewable energy development could be strongly underestimated when cut-offs are ignored.

1. Introduction

Renewable energies are often seen as a key element of the societal transformation necessary to address climate change. The scale and speed of the required energy transformation is substantial, but finding socially acceptable locations for this infrastructure can be challenging because the construction of renewable energy facilities (REFs) and associated infrastructure often faces fierce local opposition. People may hold generally positive attitudes towards renewable energy, but experience or perceive significant negative external effects and the changes they imply for landscape amenity (*e.g.* Dugstad et al., 2020; Kim et al., 2020). At the same time locating renewable energy infrastructure far away from people can limit its physical potential (Masurowski et al., 2016) and increase the cost of development and transmission (Drechsler et al., 2017). Understanding

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public's preferences towards renewable energy alternatives and quantifying the social costs of these technologies can thus help inform social decisions regarding the location of REFs and facilitate their successful and efficient expansion.

Stated preference methods such as choice experiments (CEs) are particularly well suited to measure peoples' preferences for REFs and to quantify potential negative external landscape effects (Bergmann et al., 2008; Kosenius and Ollikainen, 2013). In typical CE applications the most common assumption is that people evaluate all attributes presented to them and that people are willing to make trade-offs among all attributes (Truong et al., 2015). There is, however, some empirical evidence to suggest that people may not be willing to make trade-offs across all attribute levels, and that non-compensatory models might better represent individual choice behavior (Leong and Hensher, 2012). For example, people may have an acceptability threshold for an attribute. Beyond this threshold they might not be willing to make trade-offs. Ignoring these thresholds and assuming compensatory preferences might lead to biased welfare estimates and wrong inferences for policymaking. Li et al. (2015) find that standard random utility models could underestimate welfare measures by 30–50 % if non-compensatory choice behavior is ignored. Studies measuring preferences toward REFs could, therefore, strongly underestimate the welfare changes that would occur if new facilities are built. Consequently, value estimates would not correctly reflect opposition to new facilities explaining why the expansion of REFs such as wind power meets more vigorous opposition than studies applying the standard discrete choice model assumptions suggest.

One common method to incorporate non-compensatory choice behavior is through the use of attribute cut-offs defined as the minimum or maximum acceptable threshold level an individual states for an attribute (Huber and Klein, 1991). Findings from several studies provide evidence that individuals might state that they have attribute cut-offs, but that they are at the same time willing to violate them when making trade-offs in the CE (*e.g.* Ding et al., 2012; Peschel et al., 2016; Roman et al., 2017). Cut-off violations may occur because the minimum or maximum acceptable level of each attribute may reflect decision-makers' preferences when considered in isolation. When traded-off against other attributes, individuals may be willing to either change or violate cut-offs because the additional benefit is greater than the cost caused by the violation hence recognizing the opportunity cost of self-reported cut-offs (Swait, 2001; Bush et al., 2009).

The purpose of this paper is to measure the presence of non-compensatory choice behavior in the context of valuing renewable energy facilities and to assess to what extent this impacts on resultant welfare measures. To do so, we use data from a large-scale online stated preference survey of renewable energy involving 3,400 respondents in Germany. The CE focused on solar, biomass, and wind renewable energy systems as well as long-distance transmission lines that play an essential role in the current energy transformation debate. The CE attributes are characteristics of these REFs and include the distance of REFs to residential areas, the size of the facility, the number of facilities built in the surroundings of the respondent, the share of the landscape not used for renewable energy development and the change of the electricity bill of the household. In our analysis, we give particular attention to the distance of REFs to residential areas which is a prominent topic regarding energy expansion in Germany and other parts of the world where renewable energy expansion faces local opposition (*e.g.* Boyle et al., 2019).

Germany provides an important and useful empirical application as it has plans to substantially expand renewable energy capacity and in particular wind energy to meet ambitious targets for greenhouse gas (GHG) emission reductions to mitigate climate change (Robinius et al., 2020). Despite the importance of wind energy to a successful transformation of the energy system, the rate of installation of wind energy facilities has been decreasing over the past years (BWE, 2020). One of the reasons for a slowing expansion are local concerns over the construction of new REFs as well as new transmission lines. Recently, relatively restrictive mandatory minimum distances of wind farms to residential areas have been imposed at the regional or the state level. For instance, in 2014 the largest German federal state (Bavaria) introduced regulation that new turbines have to be installed at a distance of ten times the height of the turbines. This restriction so far led to a 90 % reduction of permits granted for wind turbine construction (Stede and May, 2020).

We use a split-sample approach in this research where respondents are randomly assigned to one of two treatments that only differed in whether cut-offs are stated or not. We first analyze whether participants state cut-offs concerning characteristics of renewable energy development. We then test whether cut-off elicitation prior to a CE has an influence on respondents' stated preferences. To our knowledge this is the first inquiry studying whether the elicitation of cut-offs prior to a CE has an impact on stated choices. Using the split-sample that we elicited attribute cut-offs from, we then investigate whether respondents stick to their self-reported constraints or whether they are willing to violate them while responding to the choice tasks. We model cut-offs in a mixed logit model in WTP space with utility penalties for violated attributes and calculate non-marginal welfare measures taking cut-off information into account. To the best of our knowledge this is the first attempt to explicitly consider attribute thresholds in the calculation of non-marginal welfare measures.

This paper contributes to the literature employing CEs to elicit preferences for renewable energy including for onshore wind sites (*e.g.* Álvarez-Farizo and Hanley, 2002; Dimitropoulos and Kontroleon, 2009; Strazzera et al., 2011; Peri et al., 2020), offshore wind sites (*e.g.* Ladenburg, 2009; Krueger et al., 2011; Ladenburg and Lutzeyer, 2012; Lutzeyer et al., 2018), different types of renewable energy sources simultaneously (*e.g.* Bergmann et al., 2008; Cicia et al., 2012; Kosenius and Ollikainen, 2013, Plum et al., 2019), and for transmission lines (McNair et al., 2011; Ju and Yoo, 2014). At the same time, we build on this literature by improving the understanding of the role of attribute cut-offs and the importance of considering them in stated preference valuation studies.

Our results can inform decision makers in the design of new policies to promote the expansion of renewable energy. For instance, if negative external effects of REFs are underestimated when cut-offs are not considered, policymakers might want to experiment with offering financial community participation in renewable energy projects or with receiving benefits via price discounts on electricity generated by turbines in people's surroundings to overcome opposition at the local level. A recent position paper by the German Federal Ministry for Economic Affairs and Energy (BMWi) brings into play, among others, both instruments for promoting local acceptance (BMWI 2020).

2. State of the art and research questions

The use of attribute cut-offs may be investigated by following either an analytical or a self-stated approach. Since the empirical implementation of the analytical method – a two-stage estimation approach (*e.g.* Manski, 1977) – involves several technical challenges (*e.g.* Swait, 2001; Ding et al., 2012), the self-stated approach has been applied more frequently in previous research. In the self-stated approach respondents are asked to state their attribute thresholds prior to or after the CE. Swait (2001) discusses merits and drawbacks of both approaches and opts for eliciting attribute cut-offs prior to the CE, arguing that thresholds should be based on individuals' experience and not on information provided in the choice tasks. However, the act of stating cut-offs may influence subsequent choices, but there is no research on the extent of these effects. Therefore, our first research question is: RQ1 - Does cut-off elicitation affect stated choices?

The use of attribute cut-offs in the context of CEs has been investigated in several areas of research including transportation research (Danielis and Marcucci 2007, Marcucci and Gatta, 2011; Hensher and Rose, 2012; Feo-Valero et al., 2016; Roman et al., 2017; Zhang and Zhu, 2019), health economics (Mentzakis et al., 2011), and food choices (Ding et al., 2012; Moser and Raffaelli, 2012, 2014; Peschel et al., 2016). As far as we are aware of there are only two studies investigating attribute cut-offs in an environmental economics context. Both focus on cut-offs with respect to the cost or price attribute. Bush et al. (2009) conduced a CE for eco-tourism using data from 419 participants who visited a national park in Rwanda. Colombo et al. (2016) used a modified cut-offs approach to detect choice inconsistencies with respect to the cost attribute. They did not directly elicit cut-offs, but instead tested for inconsistencies among the accepted cost levels of alternatives chosen while respondents made their choices in the choice sets and a subsequently stated open-ended WTP for a best program with all attribute levels at their maximum value. If the follow-up, open-ended stated WTP was lower than the cost level accepted on the choice tasks this was interpreted as a cut-off violation and respondents had the opportunity to revise their stated WTP. Another difference to the present study is that they also did not consider cut-offs for non-monetary attributes.

The stated cutoffs literature suggest that participants violate their stated-cut-offs by choosing alternatives with levels beyond their thresholds. For instance, Roman et al. (2017) report that self-imposed thresholds are violated in 6–32 percent of the choices, depending on the alternative and attribute. Peschel et al. (2016) calculated the average number of instances of cut-off violation to be 6 and higher for a total of 12 choices. Related to these observations our second research question is: RQ2 - Do people have attribute cut-offs concerning characteristics of renewable energy development and are they willing to violate them when having to make trade-offs?

The violation of thresholds leads to the soft cut-off approach first proposed by Huber and Klein (1991), who found that individuals violate their stated cut-offs and adjust their thresholds when they have more information about the attributes and the decision task. A model recognizing the idea of soft cut-offs by expanding the random utility framework and introducing utility penalties when self-imposed thresholds are violated was developed by Swait (2001). Results from applying this model indicate that the inclusion of cut-off parameters improves the fit of the model (*e.g.* Feo-Valero et al., 2016; Peschel et al., 2016) and affects marginal WTP measures (*e.g.* Bush et al., 2009; Moser and Raffaelli, 2012). Furthermore, Moser and Raffaelli (2014) observed choices to become less consistent as the number of potential violations or the number of cut-offs stated at the most severe level increased. Recently, heterogeneous use of cut-offs has increasingly gained attention. Peschel et al. (2016) as well as Roman et al. (2017) employed latent class models including cut-off parameters in transportation and food choice contexts, respectively. They found that use and violation of attribute cut-offs varied significantly across respondents due to observed – consumer involvement, gender, income (Peschel et al., 2016) – and unobserved factors (Roman et al., 2017). Similar observations were made by Zhang and Zhu (2019) using a mixed logit model to analyze preferences towards the hinterland leg transportation chain of export containers. Following Swait (2001), we also account for the heterogenous use of cut-off information to answer our third research question: RQ3 - To what extent does the inclusion of cut-off information alter model estimates?

As stated above there have been some attempts to derive marginal WTP considering attribute cut-offs. However, marginal WTP estimates will generally not be constant over the range of attribute levels as they depend on the amount of cut-off violations at the different attribute levels. Thus, constructing non-marginal welfare measures is important for properly understanding how impacts vary by changes in attributes such as distance, but we are not aware of any study calculating these type of welfare measures in a policy-relevant scenario. We aim at doing so with our fourth research question: RQ4 - Does the incorporation of cut-off information lead to different welfare measures regarding the distance to renewable energy facilities?

3. Study design and cut-off elicitation

3.1. Study design

Designing and pretesting of the survey involved three steps: The first task was to conduct a broad literature review focussing on studies using CEs to analyze preferences towards renewable energy development. Based on this a first set

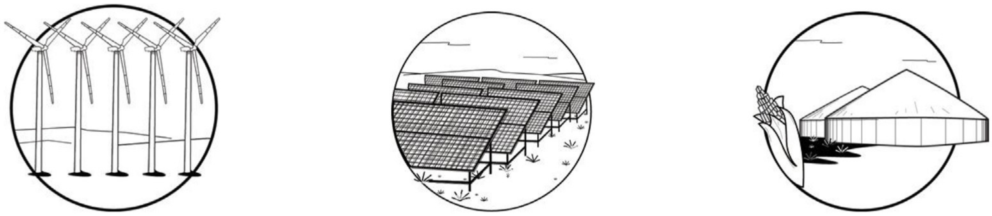

Fig. 1. Pictograms presented to respondents.

of candidate attributes was identified and an example choice set created. The second step was to conduct focus group discussions in six different cities throughout Germany. Among other things, participants were asked to answer and give feedback on parts of the questionnaire including the CE and its attributes. Participants of these focus groups were randomly recruited via telephone. Quota were imposed regarding age and gender. In the third step the questionnaire including a revised CE was tested in two pilot studies with a) colleagues as well as b) participants from the online panel of a survey company.

The final version of the questionnaire started by visualizing the renewable energy sources to be considered in the survey using pictograms (Fig. 1). The text defined the renewable energies in the survey. Hereafter, participants were asked to answer several warm-up questions, for example on their exposure to REFs or whether they feel disturbed by REFs in their surroundings. After that, respondents were asked about their attribute cut-offs (see section below). This part was followed by a detailed introduction to the CE attributes. The attributes are summarized in Table 1 including the attribute names as shown on the choice set in column 1 and the explanatory text used in the survey in column 2. Since some of the attributes are alternative-specific, column 3 states the alternative corresponding to the attribute levels and column 4 reports the alternative-specific attribute levels. Column 5 introduces the labels which are subsequently used in this paper to refer to the corresponding attribute.

In total six attributes were used in the CE. First, the attribute Distance was specified alternative-specific (attribute labels: *Distance_Wind*, *Distance_Solar*, *Distance_Biomass*) and expressed in meters (m) to the edge of town. The attribute could adopt levels of 300, 600, 900 1600 and 2500 m. The size of the facilities was described for each renewable energy source specifically (attribute labels: *Size of REFs_Wind*, *Size of REFs_Solar*, *Size of REFs_Biomass*). Focus group discussions revealed that the number of turbines (wind), the number of football (soccer) fields (solar) and the number of fermentation tanks (biogas) were suitable metrics. Next, the number of REFs within the ten-kilometer (km) surroundings could have attribute levels from one to five (attribute labels: *Number of REFs_Wind*, *Number of REFs_Solar*, *Number of REFs_Biomass*). The attribute related to the protection of the landscape view (attribute label: *Landscape*) was described as the minimum share, in percentage terms, of the landscape not used for renewable energy expansion. This area had to be a contiguous area excluded from the development of renewable energy within a radius of up to ten km around the respondent's place of residence and had the levels 10 %, 20 %, 30 %, 40 % and 50 %. This attribute was included in the CE as a result of the survey design process. In the focus group discussions several participants stated that they didn't want to be surrounded by REFs. They emphasized that they wanted to have an undisturbed view at least on a certain share of the landscape. As this was an important concern, the attribute was included to capture people's preferences for keeping parts of the landscape view free of new REFs.

The effects of expanding the electricity grid were captured by long-distance transmission lines which could be built underground or overhead (attribute label: *Transmission lines*). Finally, the payment vehicle used were changes of the electricity bill per month and household (attribute label: *Cost*).

The CE was introduced to respondents as follows: "Renewable energy as well as the electricity grid will be expanded in Germany. In the following choice sets you can choose among different alternatives of renewable energy development. Please think of renewable energy facilities to be built in the ten-kilometer surroundings of your place of residence. If you live in a large city, please consider the surrounding area of your city. You can choose among the following alternatives:

- Electricity from wind energy (wind farms)
- Electricity from solar energy (solar fields)
- Electricity from biomass (biogas power stations)

Table 1
Attributes employed in the CE.

Attribute name	Explanation given in the survey	Alternative	Attribute level	Label
Minimum distance to the edge of town	The renewable energy facilities can be installed at different distances (300 m; 600 m; 900 m; 1600 m; 2500 m) from the edge of the town.	Wind	300 / 600 / **900** / 1600 / 2500	Distance_Wind
		Solar	300 / 600 / **900** / 1600 / 2500	Distance_Solar
		Biomass	300 / 600 / **900** / 1600 / 2500	Distance_Biomass
Size of the REF	The size of the renewable energy facilities can vary (small, medium, large). It is described by the number of wind turbines, the area of solar fields measured in football pitches or the number of fermentation tanks in the case of biogas plants.	Wind	small (5–10 turbines) / **medium** (18–25 turbines), large (35–50 turbines)	Size of REFs_Wind
		Solar	small (1–10 football f.) / **medium** (20–60 football f), large (100–150 football f)	Size of REFs_Solar
		Biomass	small (1–3 fermentation tanks) / **medium** (5-8 fermentation tanks), large (15–25 fermentation tanks) **The future SQ level is medium**.	Size of REFs_Biomass
Number of REFs	New renewable energy facilities can be built at 1, 2, 3, 4 or 5 location(s) within a radius of up to 10 km from the place where you live.	Wind	1 / 2 / **3** / 4 / 5	Number of REFs_Wind
		Solar	1 / 2 / **3** / 4 / 5	Number of REFs_Solar
		Biomass	1 / 2 / **3** / 4 / 5	Number of REFs_Biomass
Protection of landscape view / minimum share of landscape not used for renewable energy expansion (in %)	Within a radius of up to 10 km around the place where you live, a contiguous area can be excluded from the development of renewable energy for the protection of the landscape (10 %, 20 %, 30 %, 40 % or 50 % of the area).		10 / 20 / **30** /40 / 50	Landscape
Long-distance transmission lines	New transmission lines are needed to transport electricity from renewable energy. They can be built as overhead lines or underground cables.		**overhead** / underground	Transmission lines
Surcharge or rebate to your electricity bill in Euros per month (year)	Depending on the alternative, your monthly electricity bill will change from 2014 on, and can range from minus €10 to plus €23 per month.		−10 (−120) / −5(−60) / +2(24) / +7(84) / +14(168) / +23(276)	Cost

Note: Levels of the future status quo are presented in bold.

- I do not care about the type of renewable energy generation (you will not have any influence on the type of renewable energy which will be developed in the ten-kilometer surroundings of your place of residence.)"

The label of each alternative was first visualized using the pictograms shown in Fig. 1. The last alternative ("I do not care") is a future status quo described by attribute levels as indicated in Table 1. Choosing this alternative indicates that respondents, compared to the other available alternatives, do not care about the type of renewable energy that would be developed in their surroundings and that they agree with the attribute levels of that alternative. For example, the minimum distance was always 900 m meaning that if people opt for this alternative, they agree that any REF could move as close as 900 m to the edge of their town. Fig. 2 gives an example of a choice set. On each choice set respondents were asked to choose their preferred alternative. After completion of the choice tasks, there was a section asking a range of attitudinal questions were presented to respondents. The questionnaire closed with a series of questions about socio-demographic characteristics.

To allocate the attribute levels across choice sets, a Bayesian efficient design optimized for multinomial logit models with labelled alternatives was generated. As an optimization criterion, the C-error was used (Scarpa and Rose, 2008). The prior values were taken from models estimated on the basis of data from the six focus groups as well as the pilot studies. The final design had 24 choice sets divided into four groups of six choice sets. Respondents were randomly assigned to one of the four blocks. The order of appearance of the choice sets was randomized. Also, the order of the first three alternatives was randomized across respondents.

3.2. *Cut-off elicitation*

Two treatments were implemented in the survey. In Treatment 1 respondents were not requested to state any cut-offs whereas in Treatment 2 attribute thresholds were elicited before the CE was introduced. Note that this was the only difference between the treatments. The respondents assigned randomly to Treatment 2 were asked to state their maximum or minimum acceptable levels regarding four out of the six attributes prior to the CE and before introducing the attributes. By asking the cut-off questions before and not after the CE, we followed Swait's (2001) argument that thresholds should be based on individuals' past experience and not on information provided in the choice tasks. Similar to Aizaki et al. (2012); Ding et al. (2012); Moser and Raffaelli (2014), pre-defined cut-off levels were presented to respondents. Respondents were asked to select the category closest to their threshold.

	Electricity from wind power	**Electricity from biomass power**	**Electricity from solar power**	**Don't care about the type of renewable energy**
Minimum distance to the edge of town	600m	2500m	300m	900m
Size of REFs	large (35-50 turbines)	large (15-25 fermentation tanks)	small (1-10 football fields)	Medium
Number of REFs	4	5	5	3
Protection of landscape view	20%	50%	10%	30%
Long-distance transmission line	underground	underground	overhead	overhead
Change of electricity bill per month (year)	+14€ (+168€)	-5€ (-60€)	+14€ (+168 €)	0 €
I choose	□	□	□	□

Fig. 2. Example choice set.

Table 2
Cut-off levels for attribute Distance.

Renewable energy facilities to generate electricity from	*Minimum distance*					
	300 m	600 m	900 m	1600 m	2500 m	I do not care about the minimum distance
wind power	○	○	○	○	○	○
Solar power	○	○	○	○	○	○
Biomass	○	○	○	○	○	○

For the attributes *Distance* and *Number of REFs*, alternative-specific thresholds were elicited since both attributes are assumed to depend on the type of renewable energy. Minimum requirements for Landscape and Transmission lines, however, were assumed to be generic. Thus, a total of eight cut-offs were elicited. The cut-off question regarding the distance to REFs was as follows: "If you think of the expansion of renewable energy, what is the minimum distance renewable energy facilities should at least have to your place of residence?". The different cut-off levels were presented, and respondents were requested to select the cut-off level most closely matching with their thresholds (Table 2).

The wording for the question concerning Number of REFs and Landscape was similar. However, for the Number of REFs question, respondents were asked to state their upper cut-off since utility is expected to be negatively influenced by this attribute. The cut-off question for the qualitative attribute Transmission lines was worded as follows: "Which statement applies to you the most?" The categories were: A) When expanding the electricity grid, new long-distance transmission lines must be built overhead. B) When expanding the electricity grid, new long-distance transmission lines must be built underground. C) I do not care whether new transmission lines are built overhead or underground.

No thresholds were elicited for the attribute Size of REFs and Cost. Concerning Size of REFs, no common metric could be used to describe the attribute, *i.e.*, number of turbines *vs.* number of football fields *vs.* number of fermentation tanks. As a consequence, these cut-off question would have added substantial complexity for respondents. Concerning the cost, we refrained from eliciting cut-offs as we had not introduced the hypothetical market at this point of the questionnaire and were worried that asking respondents for maximum cost level would raise drop-out due to protesting.

4. Empirical specification

4.1. Model estimation

The empirical specification is based on the random utility framework. A utility function U for respondent n and alternative i in choice task t is characterized by a price p attribute, a vector of non-price attributes $\boldsymbol{x}$ and a random error term ε:

$$U_{nit}(p_{it}, \boldsymbol{x}_{it}) = \alpha_n{}' p_{it} + \boldsymbol{b}_n' \boldsymbol{x}_{it} + \varepsilon_{nit}/\sigma_n \tag{1}$$

where α_n and $\boldsymbol{b}_n$ are individual-specific parameters and ε_{nit} is assumed to be extreme value distributed with scale σ_n. We use a mixed logit model specification to incorporate preference heterogeneity across respondents by allowing parameters to deviate from the population means following a random distribution while accounting for multiple responses per individual. Let the sequence of choices over T_n choice tasks for respondent n be y_n, *i.e.* $y_n = \langle i_{n1}, i_{n2}, \ldots, i_{nT_n} \rangle$.

Eq. (1) presents the mixed logit model in 'preference space'. However, given the interest in estimating WTP values for energy program attributes, we use a WTP space expression (Train and Weeks, 2005) that can be written as:

$$\sigma_n \alpha_n{}' p_{it} + \sigma_n \boldsymbol{b}_n' \boldsymbol{x}_{it} + \varepsilon_{nit} = \sigma_n \alpha_n \left(p_{it} + \boldsymbol{\beta}_n' \boldsymbol{x}_{it} \right) + \varepsilon_{nit} \tag{2}$$

where $\boldsymbol{\beta_n} = \frac{\boldsymbol{b_n}'}{\alpha_n}$ is the vector of implicit prices for the energy alternative attributes. The two model specifications in Eqs. (1) and (2) are behaviorally equivalent but can differ regarding distributional assumptions of the parameters. We assume that $\boldsymbol{\beta_n}$ is normally distributed and the price attribute α_n is log-normally distributed.

In this model the unconditional choice probability of respondent n's sequence of choices is the integral of the logit formula over all possible values of η_{ni} weighed by the density of η_{ni}:

$$\Pr\left(y_n \alpha_n, \beta_n\right) = \int \prod_{t_1=1}^{T_n} \frac{\exp\left(\sigma_n \alpha_n \left(p_{it} + \boldsymbol{\beta}_n' \boldsymbol{x}_{it}\right)\right)}{\sum_{j=1}^{J} \exp\left(\sigma_n \alpha_n \left(p_{it} + \boldsymbol{\beta}_n' \boldsymbol{x}_{it}\right)\right)} f\left(\eta_{ni} \Omega\right) d\eta_{ni}, \tag{3}$$

where $f(\eta_{ni}|\Omega)$ is the joint density of parameter vector for price and K non-price attributes $[\alpha_n, \beta_{n1}, \beta_{n2}, \ldots, \beta_{nK}]$, η_{ni} is the vector comprised of the random parameters and Ω denotes the parameters of these distributions (*e.g.* the mean and variance). This integral does not have a closed form and thus requires approximation through simulation (Train, 2009). The mixed logit models used in this paper were estimated by maximum simulated likelihood with 2,500 Sobol draws using the R package *apollo* (Hess and Palma, 2019).

Several discrete choice models have been proposed to accommodate non-compensatory preferences in general (*e.g.* Elrod et al., 2004; Martínez et al., 2009), and attribute cut-offs in particular (Swait, 2001). In a two-stage sequential choice approach, proposed by Manski (1977) and Swait and Ben-Akiva (1987), attribute cut-offs are reflected in a first stage non-compensatory choice set formation model, followed by a second stage model of compensatory decision making that evaluates the choices of the screened alternatives (Swait, 2001). This approach, however, does not explicitly use cut-off information gathered from the decision maker. Estimation using this approach is computationally intensive and does not allow for cut-off violations / penalties (Ding et al., 2012). The linear compensatory model by Swait (2001) introduces "soft" cut-offs. Violation of "soft" cut-offs translates into penalties during the evaluation of alternatives. The model therefore incorporates cut-offs as a behavioral phenomenon in the evaluation stage of the choice process (Swait, 2001).

Estimating a model with "soft" cut-offs requires addition of an additional penalty function to the utility function in WTP space that associates information on the cut-offs with the penalties. The thus extended utility function, without recognizing the sequence of repeated choices, has the following form:

$$U_{ni} = \sum_{i \in C} \delta_{ni} U(p_i, \boldsymbol{x}_i) + \sum_{i \in C} \sum_{k} \delta_{ni}(\omega_{nk}' \lambda_{nik}) \tag{4}$$

where δ_{ni} indicates the alternative chosen from the choice set containing C available alternatives, $\boldsymbol{x}_i$ is the k dimensional vector that describes the good, ω_{nk}' is the marginal implicit price of violating the cut-off for attribute k, and λ_{nik} is a cut-off constraint variable (Swait, 2001; Bush et al., 2009).

4.2. Calculation of welfare measures

Welfare measurement is more complicated for models that incorporate cut-offs because individuals' marginal utility is dependent on whether their cut-offs are violated or not. Furthermore, there are three types of cut-offs depending on the attributes and their levels. A lower limit cut-off exists if more of an attribute is generally preferred over less. Examples are distance and landscape view attributes. An upper limit cut-off exists if less of an attribute is generally preferred over more. This applies in our case to the number of REFs attribute. The third type of cut-off is a binary quality cut-off. It exists for attributes with only two levels, in our case study the attribute on transmission lines.

We assume the cut-off constraint λ_{nik} for person n and attribute X_k, given stated cut-off θ_{nk}, is defined as:

$$\lambda_{nik} = \begin{cases} \max\left(0, \theta_{nk} - X_k\right) \ \textit{if} \ \text{lower limit cut-off (distance and landscape view)} \\ \max\left(0, X_k - \theta_{nk}\right) \ \textit{if} \ \text{upper limit cut-off (number of REFs)} \\ \left|X_k - \theta_{nk}\right| \ \textit{if binary quality} \ \text{cut-off (transmission lines)} \end{cases} \tag{5}$$

Table 3
Socio-demographic characteristics of participants.

Variable	Sample: no cut-offs Mean (SD)	Sample: cut-offs Mean (SD)
Number of respondents	1696	1694
Age (years)	42.64 (14.20)	42.80 (14.00)
Gender (1 = female)	0.46 (0.50)	0.45 (0.50)
Education (years of schooling and university attendance)	14.14 (3.56)	14.03 (3.57)
Place of residence		
- Large city	0.19 (0.39)	0.21 (0.40)
- Suburban area of a large city	0.18 (0.38)	0.16 (0.37)
- Medium size or small city	0.35 (0.48)	0.33 (0.47)
- Village	0.29 (0.45)	0.31 (0.46)

Note: SD = standard deviation.

A dummy variable γ_{nk} indicating cut-off violations for individual n is then:

$$\gamma_{nk} = \begin{cases} 0 \, if \, \lambda_{nik} = 0 \\ 1 \, if \, \lambda_{nik} > 0 \end{cases} \tag{6}$$

The implicit price is based on estimated coefficients ($\beta^{'}_{nk}$, $w^{'}_{nk}$) over X_k and is assumed to depend on whether the stated cut-off is violated or not:

$$\frac{\partial U_{nk}}{\partial X_k} = \begin{cases} \beta_{nk} + \omega_{nk} \, if \, X_k < \theta_{nk} \\ \beta_{nk} \, if \, \theta_{nk} \leq X_k \end{cases} \tag{7}$$

Thus, for each individual n, the implicit price can be estimated as:

$$\frac{\partial U_{nk}}{\partial X_k} = \beta_k + \gamma_{nk}\omega_{nk}. \tag{8}$$

Whether the stated cut-off is violated or not for X_k at a given level l ($l = 1, 2, \ldots, L$) varies across individuals. Therefore, sample level mean implicit prices that take cut-off violations into account must consider the share of the sample that violated their stated cut-off for the L levels of X_k. In other words, the presence of an individual-specific utility penalty implies that there is no unique mean implicit price for X_k ; rather, the mean implicit price depends on the point along X_k at which marginal utility is evaluated, with varying shares of cut-off violations along X_k across the sample.

For continuous attributes, we now define j intervals t_{jk} between the L levels of the continuous attribute X_k (in our case $J = L$), such that all values within the attribute level range of X_k are represented by the intervals. For example, consider the distance attribute denoted as d where the intervals are defined as:

$$t_{1distance} = [300, 300]; \; t_{2d} = (300, 600]; \; t_{3d} = (600, 900]; \; t_{4d} = (900, 1600]; \; t_{5d} = (1600, 2500].$$

The first interval is defined for the point 300 to capture people who indicate 300 as their minimum distance threshold. Let $\Phi(t_{jk})$ be the cumulative share of the sample that violates their stated cut-off at interval t_{jk}. Note that for lower limit cut-off violations (as is the case for the distance attribute), the cumulative share is estimated from the j th interval to J, and *vice versa* for upper limit cut-offs. The mean implicit price across the sample for a point within the attribute level range falling into one of the J intervals is then estimated as:

$$\frac{\partial U}{\partial X_k} = \beta_k + \Phi(t_{jk})\omega_k; \; \forall X_k \in \; t_j. \tag{9}$$

We use this expression to calculate welfare estimates for changes by re-defining the intervals based on differences in the attribute levels relative to the future status quo. For example, for the distance attribute, the status quo level is 900 m. Therefore, we subtract 900 from all the distance intervals.

5. Results

5.1. Descriptive statistics of the survey

In total 3,400 respondents completed the online survey. After data cleaning 3,390 useable interviews remained and are used in the subsequent analysis. Of the total number of participants 1,694 respondents faced the cut-off questions (Section 2.2). 1,696 people were not asked to state their cut-offs. Mean age was measured to be 43 years for the non-cut-off sample (also around 43 years for the cut-offs sample) while 46 % (sample without cut-offs) and 45 % (sample with cut-offs) of the respondents were females (Table 3). The average level of education, which is expressed in years of school and university attendance, was around 14 years for both treatments. With respect to the place of residence 19 % of the respondents lived in

Table 4
Frequency of alternatives chosen across split samples.

Alternative	Sample: no cut-offs	Sample: with cutoffs
Wind	2906 (28.56 %)	2810 (26.67 %)
Solar	3959 (38.91 %)	4114 (40.48 %)
Biomass	2205 (21.67 %)	2179 (21.44 %)
Future status quo	1106 (10.87 %)	1061 (10.44 %)
Total	10176 (100 %)	10164 (100)

Table 5
Comparison of WTP estimates across split samples.

Parameter	Mean		Interaction term		Standard deviation	
	Coef.	(|t-ratio|)	Coef.	(|t-ratio|)	Coef.	(|t-ratio|)
ASC_Wind	−0.97	(0.68)	−2.32	(1.17)		
ASC_Solar	16.68*	(12.56)	−2.02	(1.08)		
ASC_Biomass	−0.37	(0.26)	−3.26	(1.58)		
Distance_Wind	0.49*	(7.67)	0.17*	(2.03)	0.94*	(12.94)
Distance_Solar	0.11	(1.94)	0.14	(1.72)	0.85*	(17.27)
Distance_Biomass	0.25*	(4.11)	0.08	(0.98)	0.95*	(11.68)
Size of REFs_Wind (small)	−0.29	(0.18)	0.27	(0.14)	29.58*	(21.25)
Size of REFs_Solar (small)	4.57*	(4.09)	1.46	(0.92)	16.84*	(13.43)
Size of REFs_Bio (small)	2.19	(1.66)	1.39	(0.76)	9.52*	(6.36)
Size of REFs_Wind (large)	−2.96*	(2.86)	−0.04	(0.02)	8.50*	(6.42)
Size of REFS_Solar (large)	−2.34*	(2.24)	−0.81	(0.55)	8.61*	(6.14)
Size of REFs_Bio (large)	−1.03*	(2.79)	1.23	(0.84)	8.43*	(3.62)
Number of REFs_Wind	0.50	(1.32)	−0.35	(0.66)	5.47*	(17.95)
Number of REFs_Solar	−1.36*	(4.07)	0.34	(0.70)	4.80*	(20.57)
Number of REFs_Bio	−1.21*	(2.74)	0.28	(0.48)	5.65*	(22.91)
Landscape	0.06*	(3.51)	0.17*	(6.80)	0.28*	(10.15)
Transmission lines (underground)	7.31*	(12.34)	2.17*	(2.67)	10.32*	(22.37)
Cost	−2.05*	(36.54)	0.77*	(10.18)	0.00	(0.09)
Log-likelihood (0)	28197					
Log-likelihood (final)	21270					
BIC	43047					

Note: Coef. =coefficient; Reference for dummy variables Size is medium; BIC = Bayesian Information Criterion; an asterisks marks coefficients significant at the 5 %-level or higher.

large cities, 18 % in sub-urban areas of large cities, 35 % in medium sized or small cities, and 29 % in villages. The corresponding proportions for the sample without cut-offs are 21 %, 16 %, 33 % and 29 %, respectively. For each variable a two-sample *t*-test of equal means was conducted (Table 3). The null hypothesis of equal means could not be rejected in any case. Compared to the German national average the total sample consists of a very large share of respondents with a university degree. This introduces a bias towards people in higher education. Since the aim of the paper is not to aggregate WTP estimates, this issue is of minor concern for our research questions.

5.2. Landscape externalities across treatments

As part of the analysis of the influence of cut-off elicitation questions on preferences, we compare the frequency of the alternatives chosen in Treatment 1 with the frequency of alternatives chosen in Treatment 2. Given that each respondent faced six choice sets, the data comprises of 10,176 choices in the sample without stated cut-offs and 10,164 choices in the sample with stated cut-offs. “Electricity from solar power” was the most frequently chosen alternative (38.9 % treatment without cut-off elicitation, 40.5 % treatment with cutoffs), followed by wind power (28.6 % and 26.6 %) and electricity from biomass (21.7 % and 21.4 %). Participants opted for the future status quo in 10.9 % (no cut-off elicitation) and 10.4 % (with cut-off elicitation) of the choice sets. As already mentioned, choosing the future status quo indicates that individuals would not have any influence on the type of renewable energy that will be developed in their ten-kilometer surroundings. Moreover, participants who were asked to state their attribute thresholds chose the solar alternative slightly more often than respondents who were not required to report their cut-offs (Table 4). The opposite effect is observed for wind power, electricity from biomass and the future status quo. We conducted a chi-squared test with the null-hypothesis being that the frequency of chosen alternatives is independent of the sample that participants were randomly assigned to, *i.e.*, with and without cut-off elicitation. As a result we cannot reject our null hypothesis at the five per cent level of significance (p = 0.13).

Table 5 presents estimates of landscape externalities from renewable energy development across treatments using mixed logit models in WTP space. Here and in the following presentations we consider the five percent level of significance. We used interaction terms between the attributes and each time an indicator variable for cut-off elicitation. The indicator variable takes the value of one if the respondent was assigned to the sample that included cut-off questions and a value of zero otherwise.

In the following, we first consider the main effects of the model results. Estimates of the alternative-specific constants (ASCs) suggest that respondents prefer, independently of the attributes, solar power over the future status quo. No significant influences are observed with respect to the constants for wind and biomass power. For a 100-meter increase in the distance to wind farms respondents are, on average, willing to pay 0.49 EUR per household and month. The corresponding figure for biomass facilities is 0.25 EUR. The effect of the distance to solar fields is not significantly different from zero. For a decrease in the size of the solar field from medium to small, participants are willing to pay 4.57 EUR. The corresponding effects for size of wind and biomass power facilities are statistically indistinguishable from zero. However, respondents require compensation for an increase in the size of the REFs for all types of REFs (2.96 EUR (wind); 2.34 EUR (solar); 1.03 EUR (biomass)). With respect to the number of REFs, no significant effect is observed with respect to wind farms. An explanation for this might be that the most important issue for respondents with respect to wind farms is to have them located further away; compared to this, the number of wind REFs within a ten-kilometer radius might not be perceived as important. In contrast to the case of wind power, WTP for a greater number of solar and biomass facilities is estimated to be negative with values of −1.38 EUR (solar) and −1.26 EUR (biomass) for an increase of one facility in the ten-kilometer surroundings. For the contiguous share of the landscape that is not used for future renewable energy expansion surrounding the respondents' place of residence, mean marginal WTP amounts to 0.06 EUR / per cent. This attribute was meant to capture concerns about being surrounded by REFs. Participants are, on average, willing to pay 7.31 EUR per month and household to have long-distance transmission lines built underground rather than overhead. This finding reflects the great importance of the layout of new transmission lines in the public debate on expanding renewable energy.

Accounting for the interaction effects mean marginal WTP is significantly higher if cut-off information is collected in the survey for three attributes - *Distance_Wind*, *Landscape* and *Transmission lines.* This effect is particularly pronounced for *Landscape*. WTP for this attribute increases almost four-fold from 0.06 EUR to 0.23 EUR if respondents stated their attribute thresholds prior to the CE. The corresponding increase in WTP for attributes related to the distance to wind farms and long-distance transmission lines is +0.17 EUR and +2.17 EUR, respectively. As suggested by the estimated standard deviation (last column of Table 5), a large degree of unobserved preference heterogeneity is detected in the sample. Except for large bioenergy facilities, all standard deviation estimates are highly significant. Lastly and in addition to the WTP values, the estimated preference parameter for cost reveals that the likelihood of choosing an alternative decreases with the cost of the option.

5.3. Cut-off analysis

5.3.1. Descriptive statistics

The vast majority of respondents[1] stated that they had minimum (maximum) Thresholds for non-monetary attributes (Table 6). About 90 % of participants register a threshold for the *Landscap*e attribute followed by the minimum distance to wind farms (roughly 85 %). A comparatively low share of 54 % of participants stated attribute constraints regarding transmission lines and the maximum number of solar fields. The highest share of respondents who stated their cut-off at the highest level is 54.1 % for the *Landscape (50 %). This is followed by the* minimum distance to REFs in the case of biomass (2,500 m) with a share of 40.7 %. Compared to wind and biomas, cut-off frequency tends to be lower for electricity from solar power for the alternative-specific attributes.

Many participants are, however, willing to violate their self-stated cut-offs when facing trade-offs against other attributes of renewable energy expansion (Table 7). Along the sequence of six choice sets, respondents opted in 39.2 % (wind), 17.4 % (solar) and 43.0 % (biomass) of the choices for an alternative with a distance level that was lower than the self-stated minimum. The percentage of choices in which the number of REFs of the chosen alternative exceeded the self-stated attribute constraint was 29.7 % (wind), 21.6 % (solar) and 37.9 % (biomass). The highest frequency of cut-off violation is found for the attribute *Landscape*. For this attribute, 51.1 % of the choices involved a cut-off violation. The corresponding figure for the attribute *Transmission Lines* is 22.4 %.

5.3.2. Effect on model results

We proceed with the results of the mixed logit model (Table 8), again estimated in WTP space, in which cut-off violations are integrated as utility penalties (Swait, 2001). Compared to the model results presented in Table 5, the inclusion of cut-off parameters changes results substantially. First, six out of eight coefficients related to penalties for cut-off violations are significantly different from zero. This reveals that attribute thresholds play a role for the choice among different renewable energy alternatives. Second, the mean coefficients of the attributes *Number of REFs* (biomass) and *Landscape* are not significantly different from zero. This highlights that including cut-off information into the choice model substantially affects results and subsequent interpretation.

When inspecting the mean effect of an attribute and its corresponding cut-off parameter, four patterns might emerge:

[1] Henceforth, the analysis reported only concerns responses from participants who answered the cut-off elicitation questions.

Table 6
Percentage of cut-off statements.

Cut-off	Wind	Solar	Biomass	Generic attributes
Minimum distance				
I do not care	14.82	38.55	16.06	
300 m	4.90	20.13	4.07	
600 m	8.15	10.63	7.85	
900 m	17.47	12.51	13.70	
1600 m	19.30	8.80	17.59	
2500 m	35.36	9.39	40.73	
Maximum number of REFs				
I do not care	33.94	45.75	32.82	
5	9.68	14.23	3.78	
4	5.19	6.73	2.30	
3	14.82	12.28	10.33	
2	15.53	10.15	15.64	
1	20.84	10.86	35.12	
Minimum share of Landscape				
I do not care				9.80
10 %				3.13
20 %				5.73
30 %				15.11
40 %				12.10
50 %				54.13
Transmission lines				
I do not care				45.95
Overhead				2.01
Underground				52.04

Table 7
Percentage of cut-off violation along the six choice sets.

Attribute	Wind	Solar	Biomass	Generic attributes
Minimum distance	39.24	17.35	42.99	
Maximum number of REFs	29.73	21.58	37.90	
Minimum share of landscape				51.08
Transmission lines				22.42

Table 8
Accounting for attribute cut-offs using the Swait (2001) approach.

Parameter	Mean attribute Coef.	(|t-ratio|)	Mean cut-off Coef.	(|t-ratio|)	SD attribute Coef.	(|t-ratio|)	SD cut-off Coef.	(|t-ratio|)
ASC_Wind	−0.15	(0.10)						
ASC_Solar	12.84*	(8.57)						
ASC_Biomass	−7.33*	(3.88)						
Distance_Wind	0.32*	(4.79)	−0.93*	(10.72)	0.81*	(15.30)	0.98*	(7.11)
Distance_Solar	0.08	(1.26)	−0.74*	(6.86)	0.47*	(10.17)	0.94*	(4.91)
Distance_Biomass	0.21*	(2.87)	−0.44*	(5.79)	0.93*	(13.89)	0.82*	(7.49)
Size of REFs_Wind (small)	1.08	(0.68)			28.90*	(16.27)		
Size of REFs_Solar (small)	4.72*	(4.73)			16.00*	(11.88)		
Size of REFs_Biomass (small)	3.15*	(2−49)			6.57*	(4.98)		
Size of REFs_Wind (large)	3.00*	(2.12)			7.26*	(2.19)		
Size of REF_Solar (large)	−4.65*	(3.86)			4.46	(1.21)		
Size of REFs_Biomass (large)	3.77*	(3.34)			12.32*	(5.07)		
Number of REFs_Wind	−0.16	(0.48)	−0.76	(1.02)	4.34*	(13.63)	5.91*	(7.51)
Number of REFs_Solar	−1.52	(1.52)	−0.51	(0.88)	3.40*	(13.50)	3.08*	(4.03)
Number of REFs_Biomass	0.19	(0.40)	−1.86*	(3.16)	4.72*	(13.24)	7.93*	(14.95)
Landscape	0.06	(1.90)	−0.24*	(6.29)	0.05	(0.98)	0.39*	(8.49)
Transmission lines (underground)	4.37*	(6.19)	−9.14*	(9.64)	7.58*	(10.39)	6.49*	(2.56)
Cost	−1.92*	(23.07)			0.90*	(4.42)		
Log-likelihood (0)	14090							
Log-likelihood (model)	10319							
BIC	21089							

Note: Coef. =coefficient; SD = standard deviation; Reference for dummy variables Size is medium; BIC = Bayesian Information Criterion.

Table 9
Marginal willingness to pay estimates in EUR without and with cut-off values.

Attribute	Scenario	Cut-off values	mean WTP	z-value	95 %-CI (lower / upper)	
Distance_wind	A	Without	−7.40	4.87	−10.40	−4.42
		With	−39.70	14.50	−44.24	−33.62
	B	Without	14.82	4.87	8.84	21.10
		With	37.93	13.09	32.25	43.61
Distance_Solar	A	Without	−1.93	1.27	−4.90	1.05
		With	−13.38	7.33	−16.96	−9.81
	B	Without	3.86	1.27	−2.10	9.81
		With	22.26	6.79	15.83	28.68
Distance_Biomass	A	Without	−4.83	2.84	−8.17	−1.49
		With	−29.81	7.27	−37.84	−21.77
	B	Without	9.66	2.84	2.99	16.33
		With	20.46	6.18	13.97	26.95

Note: The status quo distance for all scenarios is 900 m. Scenario A considers moving the REFs 450 m closer and Scenario B considers moving the REFs 900 m further away; CI = Confidence interval.

1) The parameter of the attribute and corresponding parameter of the cut-off are significant.
2) The parameter of the attribute is significant, but not the corresponding cut-off penalty.
3) The parameter of the attribute is not significant, but the corresponding cut-off penalty is significant.
4) Neither the attribute parameter nor the corresponding cut-off parameter is significant.

Distance_Wind, *Distance_Solar* and *Transmission lines* follow the first category. Taking the example of the distance to facilities generating electricity from wind, marginal WTP is estimated to be 0.32 EUR for an increase of the distance by 100 m. This value increases, on average, by 0.93 EUR per 100 m to avoid cut-off violation. There is no instance of pattern 2). The attributes *Distance_Solar*, *Number of REFs_Biomass*, and *Landscape* fall into the third category. For instance, mean WTP for the contiguous share of protected landscape from future renewable energy development is not significantly different from zero, whereas the WTP to avoid violation of the self-imposed cut-off is observed to be 0.24 EUR for every percentage point change, on average. In such cases, respondents appear to be insensitive to changes in an attribute unless their minimum requirements are violated.

Regarding the attribute *Number of REFs* (biomass), the mean attribute parameter is not significantly different from zero, but the standard deviation is large in magnitude and significant. Some respondents may have a positive association with biomass power and primarily relate energy from biomass as a source of ‘clean’ energy, while other respondents may largely perceive biomass plants as a disamenity. Across respondents, however, cut-off violations regarding the number of biomass plants result in a significant utility penalty. Comparing this to the results presented in Table 5, where the attribute *Landscape* was highly significant, one can conclude that the inclusion of cut-off information not only impacts the effect size, but also the level of significance and derived conclusions. Concerning the number of solar and wind facilities, respondents do neither care about the attribute, nor about violations of their stated cut-offs. With respect to the main attributes, the standard deviation estimates of the attribute effects and of the eight cut-off parameters provide substantial support for a large degree of unobserved preference heterogeneity across respondents (Table 8). Also, the WTP penalty varies significantly across participants due to unobserved factors.

5.3.3. *Effect on willingness to pay measures*

There is a substantial difference in WTP depending on whether cut-off values are accounted for or not (Table 9). We illustrate this for arguably one of the most debated attributes of renewable energy development – the distance of facilities to residential areas. To do so we use two scenarios: Compared to the future status quo of 900 m, Scenario A considers moving REFs 450 m closer to the place of residence (halving the distance). By contrast, Scenario B assumes that REFs will be built 900 m further away from the status quo (doubling the distance).

For all three types of REFs, we find significant differences in WTP estimates. Moreover, the differences are clearly asymmetric for an increase or a decrease relative to the future status quo. The increase in disutility for reducing the distance between REFs and settlements is greater in absolute terms than the increase in utility of moving them further away. This is most obvious for wind energy. If cut-off values are accounted for, the value is −39.7 EUR, on average, for Scenario A, while it is only −7.4 EUR when the cut-offs are disregarded. In contrast, utility increases from 14.8 EUR without consideration of cut-offs when distance is doubled (Scenario B) to 37.9 EUR when cut-off values are considered. This pattern is also observable for the remaining two REFs. In the case of solar power, WTP values are only significantly different from zero if cut-offs are considered. Halving the distance to settlements as part of a renewable energy policy would, *ceteris paribus*, result in a welfare loss of 13.4 EUR, which is much lower than the equivalent estimate for wind power. Reducing the distance to closest biomass plants would reduce welfare by 29.8 EUR, while increasing distance to 1,800 m would yield 20.5 EUR, both estimated considering cut-offs. Biomass plants are associated with the lowest WTP estimate for increasing distance of all REFs considered.

6. Discussion and conclusions

The results show that for wind farms respondents clearly prefer REFs to be constructed further away from the edge of their town or city. Also, biomass facilities are preferably constructed further away. In contrast, respondents do care much less about the distance to solar facilities, which were the most preferred renewable energy alternative. They further prefer, for example, to keep larger shares of the landscape in their surroundings free of renewable energy development. Also, individuals have a clear preference for building new long-distance transmission lines underground instead of overhead. However, the cost-benefit appraisals of renewable energy expansion projects would have to demonstrate whether benefits outweigh the costs. Moving turbines further away, for example, could limit the overall potential of electricity generation from wind power (Masurowski et al., 2016). Having transmission lines at long distances underground causes huge costs compared to installing transmission capacity overhead. To what extent the benefits would be greater than these costs is unclear at the moment.

We elicited attribute cut-offs for two alternative-specific and two generic attributes resulting in a total of eight cut-off values. To investigate whether prior cut-off elicitation affects stated preferences (research question RQ1), cut-off information was only collected from half of the sample (Treatment 2). We find that requesting cut-off information influences subsequently elicited preferences. Specifically, cut-off elicitation prior to valuation tasks affects WTP estimates for some of the attributes. For one of these attributes—the contiguous share of the landscape not used for future renewable energy development—mean WTP was found to be four times higher when respondents had previously stated attribute thresholds. An explanation for these effects is that explicitly asking participants on attribute constraints might have led to preference construction and preference learning based on cut-off elicitation questions. Simon et al. (2004) observed that preference construction often takes place by satisfying thresholds or constraints. In the next step, this might have induced respondents to accept higher levels of the cost attribute to avoid violating their self-imposed attribute constraints. An alternative explanation is that prior elicitation of cut-offs reduced strict lexicographic behavior or protesting. The cut-off elicitation offered a straightforward way to respondents to express their preferences regarding changes in attributes. Understanding the mechanisms underpinning order effects related to eliciting cut-offs, or more generally supporting information, prior to the choice tasks or afterwards remains an essential topic for further investigation (see also Liebe et al., 2018).

In response to our research question RQ2, we find that a large majority of respondents had attribute thresholds, and that the violation of self-imposed thresholds was common. Stated cut-offs were most severe for the attribute related to the share of the landscape protected from future renewable energy expansion and the alternative-specific attributes for electricity from wind and biomass power. The finding of widespread cut-off violation is in line with previous research (*e.g.* Peschel et al., 2016; Roman et al., 2017). An explanation for choosing alternatives that violate self-stated cut-offs is that thresholds elicited in isolation may not represent true preferences when making more complex decisions involving trade-offs across multiple attributes. Individuals may be willing to either change or violate cut-offs once they recognize the opportunity cost of adhering to their self-reported cut-offs, because the additional benefit of violating the cut-off is greater than the related cost (Swait, 2001; Bush et al., 2009).

In the context of our study, the willingness to violate self-reported cut-offs has important policy consequences. For instance, people are willing to accept smaller distances to wind farms when compensated by lower electricity bills. Other reasons for cut-off violations, however, may be due to the design of the present CE. One driver might have been the future status quo alternative. Although the cost of choosing this alternative was zero, participants still had to accept the levels of the other attributes. For example, the contiguous share of the landscape not used for future renewable energy development shown on the future status quo was always 30 %. This figure is lower than the stated minimum requirement of approximately two-thirds of the respondents. Another issue might have been the definition of the *Landscape* attribute. Compared to attributes such as distance of REFs or whether to build transmission lines over- or underground, it is not as clearly conceptualized and quantified. This is partially due to the nature of this attribute. Using visualization could have helped, but as the effect of REFS on the landscape view is site specific, and we were conducting a nationwide survey, using standardized visualizations could have biased estimates as well. Being aware of the potential problems this attribute might have caused, we only rely on the distance attribute to demonstrate the effect of cut-offs on welfare measures. Given the experience from the focus groups, however, we are convinced that not including the impact on the landscape view, even with a less clearly conceptualized and quantified attribute, would have caused other problems such as an omitting variable bias.

To account for the effect of cut-off violations in the choice model, we specified a mixed logit model in WTP space following the idea of soft cut-offs proposed by Swait (2001). To answer research question RQ3, we find – again in line with other studies that including the cut-off information into the model substantially impacts on model estimates. Many of the cut-off parameters have turned out to be significant indicating that cut-offs and their violations are relevant in the choice process. The results indicate that respondents employed threshold-based non-compensatory decision strategies. However, as Peschel et al. (2016) or Roman et al. (2017) show, such behavior varies significantly across respondents due to unobserved factors. Including cut-off parameters is a way of introducing non-linearity in the utility surface of related attributes. It might thus be argued that cut-off parameters are just another way of capturing non-linearity in preferences, for example, due to diminishing marginal utility. Indeed, we cannot separate different motivations that manifest themselves in non-linear patterns where marginal utility changes, often rapidly, as attribute levels change. However, we argue that identifying significant utility penalties of considerable magnitude for individual-specific cut-off violations in a model suggests that it is highly likely that threshold effects implied by cut-offs indeed provide information on threshold effects as intended.

For the fourth research question (RQ4), we find that accounting for attribute cut-offs in the modelling of choices substantially affects WTP estimates. If attribute cut-offs are accounted for, the marginal welfare measures are much higher compared to the case where no threshold information is used. This finding supports the results presented by Li et al. (2015), who also found an increase in welfare measures when accounting for non-compensatory choice behavior. It also reconfirms the need to consider the elicitation and use of attribute cut-offs carefully, especially in contexts where respondents are not familiar or have limited experience with the good or service valued. Most remarkably, our research demonstrates that ignoring cut-off information when it is relevant can have profound implications for project and policy appraisal. Using distance to wind farms as an example, we show that ignoring cut-offs has substantial impacts on welfare measures and thus might affect results of cost-benefit analysis of policies even in cases where proposed changes are relatively small.

An extension of the Swait model (2001) used in this paper could consider non-linearity in cut-off penalties for continuous attributes to indicate increasing severity of the marginal penalty as the violation of a cut-off increases. The Swait model assumes that attribute cut-offs are exogenous to the choice process. As pointed out by Ding et al. (2012) or Moser and Raffaelli (2014), cut-off endogeneity is potentially an important issue that requires further investigation. Moreover, this study requested cut-offs by asking respondents to choose from a range of discrete levels. Further research might study the effect of different elicitation formats. An alternative could be to ask open-ended questions, or to use a combination of approaches.

Another avenue for further research is the relationship between spatial preference heterogeneity and cut-offs. The attributes related to renewable energy expansion carry a spatial dimension related to, for example, existing types and amounts of renewable energy facilities across Germany. Spatial welfare patterns may thus be likely to exist and can be modelled using a range of available approaches (Glenk et al., 2020). It is conceivable that stated cut-offs also depend on observed or unobserved spatial factors. If related to observed spatial characteristics, this may offer opportunities for the development of instruments to address endogeneity concerns related to the inclusion of stated cut-offs in choice models. While a detailed investigation of spatial heterogeneity and cut-offs is beyond the scope of this paper, we estimated a model that considered preference heterogeneity related to respondents' place of residence (large city, edge of large city, medium or small city, village). The results suggest that WTP of some attributes is significantly affected by place of residence. However, the majority of cut-off parameters remain significant and still have a large impact on WTP estimates. This implies that the main findings of this paper can be maintained.

The research findings have major implications for energy policy. The construction of new REFs such as wind turbines is seen as a backbone of future electricity supply (Robinius et al., 2020). Decision makers need to weigh the social costs and acceptability of locating REFs near people, as estimated in this paper, against the costs of setting minimum distance restrictions that may strongly confine the available land for building new turbines (Masurowski et al., 2016). Otherwise, countries such as Germany might risk not meeting their climate policy objectives, which rely on large scale energy transformations. The importance of increased renewable electricity generation becomes even more evident when considering rapidly growing decentralised electricity demand related to increasing electromobility. For example, switching three quarters of the German passenger car fleet to electric vehicles would require additional electricity of 85−100 TWh per year. To provide this energy from wind power, approximately 10,000 wind turbines of the latest generation would have to be installed (Öko-Institut e. V., 2018). Finding economically viable and acceptable locations for such an ambitious number of turbines would be challenging given the acceptability thresholds found in this study. However, the fact that people seem to be willing to violate these thresholds indicates that there exists a potential for negotiation through compensation mechanisms such as rebates on electricity bills. Exploring the use of such options is an attractive strategy for ensuring a successful transformation not only of the German energy system.

Author statement

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Declaration of Competing Interest

The authors report no declarations of interest.

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